

Pre-entry Variables Related to Retention in Online Distance Education

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This study identified pre-entry variables related to course completion and noncompletion in university online distance education courses. Four hundred and sixty-four students who were enrolled in online distance education courses participated in the study. Discriminant analysis revealed six pre-entry variables were related to retention, including cumulative grade point average, class rank, number of previous courses completed online, searching the Internet training, operating systems and file management training, and Internet applications training. Results indicate prior educational experience and prior computer training may help distinguish between individuals who complete university online distance education courses and those who do not.

Online distance education has become integral to the mission of higher education institutions as a means for providing access to education for countless underserved individuals (Belanger and Jordan 2000; Carr 2000; Kearsley 2000). Yet, as online courses continue to be developed, many suggest a major challenge lies in the retention of students in these courses (Carr 2000; Cookson 1990; Gibson 1996; Osborn 2001). Anecdotal evidence and individual institution studies suggest online distance education course-completion and program-retention rates are low (Carr 2000; Phipps and Merisotis 1999). Pre-entry student attributes, such as prior computer experience, confidence, and training as well as prior educational experience are believed to increase persistence rates in online courses because students are better prepared to learn via computer technologies (Lim 2001; Osborn 2001). Yet, until relationships between retention and pre-entry at-

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tributes are more clearly identified, steps will not be taken to help at-risk students complete online courses and drop-out rates may remain high.

Background

Tinto (1975) developed a predictive model of higher education retention that is the most widely cited and tested empirically (Kember 1989). Tinto's model identified student interaction with the institution (both academically and socially) and external factors such as student goals, student commitments, and pre-entry attributes as playing a significant role in course completion. Kember adapted Tinto's model to distance education by focusing on external factors at the center of persistence in distance education. Traditional attrition research suggests retention should be studied holistically. Yet, looking at attrition in this manner can be crippling. Therefore, recent distance education studies have focused on the manageable area of pre-entry attributes, including skills, abilities, and prior education (Lim 2001; Osborn 2001).

Many variables have been hypothesized to be related to retention in online distance education courses. Much of the literature on retention was based on the premise that preparation through prior educational experience (e.g., previous distance education courses, education level, grade point average) and prior computer experience (e.g., extended orientation, training in the use of distance education technologies) are related to retention (Billings 1988; Gibson 1996; Hansen 2000; Lim 2001; Osborn 2001; Wlodkowski, Mauldin, and Gahn 2001). Several recent studies have identified relationships between persistence and the aforementioned variables (Hansen 2000; Lim 2001; Osborn 2001; Wlodkowski, Mauldin, and Gahn 2001).

Purpose of the Study

This study was undertaken to further identify pre-entry variables related to course completion by developing a predictive model of student retention in online distance education courses. An awareness of these variables may help instructors and administrators to provide appropriate assistance to at-risk students. The following research question guided this study:

Are there pre-entry variables—such as prior computer experience or prior educational experience—that distinguish individuals who complete university online distance education courses from those who do not?

Method

This study sought to gather evidence from online distance education students that would lead to general conclusions about relationships between course completion and student pre-entry variables using a quantitative research design. A simple random sample was drawn from the accessible population of students taking online distance education courses at Utah State University during the spring semester of 2003. The sampling frame included students registered in courses offered from a variety of academic departments.

Selected participants were mailed a research questionnaire that included pre-entry items hypothesized to be related to retention in online distance education courses. At the end of the semester, enrollment information was collected from the university's Continuing Education Registration Office for each student who agreed to participate in the study. Course completion data was combined with the survey data for analysis.

The study research questionnaire was developed, tested, and reviewed by a panel of distance education professionals. Based on their feedback, slight revisions were made to the survey. During the fall semester of 2002, a pilot study was conducted on a sample of individuals from the population of students taking online distance education courses at Utah State University ($N = 50$). The pretest form of the survey included an area for respondents to make criticisms and recommendations for improving the questionnaire. Based on the feedback of respondents, minor variations were made to the formatting of the questionnaire. Suggestions related to grammatical structure and item rewording were taken to ensure readability and usefulness to research goals.

Results

One thousand students taking online distance education courses were randomly selected to receive the research survey. A total of 507 surveys were returned for a response rate of 51%. Of those surveys returned, only 43 were deemed unusable due to missing data. These surveys were eliminated from analysis. Thus, a 46% usable survey response rate was achieved. Using the data collected from respondents, descriptive statistics were generated to identify the appropriate group to whom statistical inferences apply.

Students enrolled in online distance education courses ($N = 464$) participated in the study. Nearly two-thirds ($n = 293$) of the sample were female and one-third ($n = 171$) were male. Respondents ranged from 17 to 59 years old, with the average age being 29. The current class rank reported by re-

spondents included freshman (1%), sophomore (16%), junior (37%), senior (23%), masters (18%), and other (5%). The cumulative grade point averages of the respondents ranged from 1.5 to 4.0 ($M = 3.37$, $SD = .51$). The average number of previous courses completed online was 1.48 ($SD = 2.37$); the maximum number of previous courses completed was 20 and the minimum modal score was zero.

Respondents reported having zero to thirty years of computer experience with the sample average at 9.2 years ($SD = 4.66$). The number of computer training courses students had completed ranged from zero to five courses for each respective topic, including (a) searching for information on the Internet ($M = .47$, $SD = .54$, range 0–2), (b) operating systems and file management ($M = .65$, $SD = .74$, range 0–5), and (c) Internet applications including e-mail, file transfer protocol (FTP), and the World Wide Web ($M = .44$, $SD = .58$, range 0–4). Descriptive statistics for each indicator variable in relationship to course completion were also calculated and are displayed in Table 1.

Discriminant analysis was used to determine the best predictors of retention in online distance education courses as defined by course completion or course noncompletion. Seven pre-entry variables contributed to the discriminant function ($\chi^2 = 43.47$, 7 *d.f.*, $p < .0001$). Table 2 displays the structure matrix resulting from this procedure. The product-moment correlation coefficients indicate the relative ability of each of the seven variables to discriminate between completing and noncompleting students. The results of the discriminant analysis suggest these seven variables accounted for 9% of the variability in course completion (see Table 3). Table 4 shows

Table 1. Means and Standard Deviations for Indicator Variables

Variable	Completing Students ^a		Noncompleting Students ^b		Entire Sample ^c	
	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
Cumulative grade point average	3.41	0.48	3.06	0.63	3.37	0.51
Class rank	4.36	1.17	3.59	1.50	4.28	1.23
Previous courses completed online	1.57	2.47	0.79	1.10	1.48	2.37
Years of computer experience	9.26	4.57	8.69	5.30	9.20	4.67
Operating systems and file management training	0.67	0.76	0.43	0.57	0.65	0.74
Internet applications training	0.46	0.59	0.28	0.46	0.44	0.58
Searching the Internet training	0.50	0.54	0.30	0.46	0.47	0.54

^a $n = 411$. ^b $n = 53$. ^c $N = 464$.

Table 2. Discriminant Function Structure Matrix

Indicator of Completion	Coefficient
Cumulative grade point average	0.707
Class rank	0.643
Searching the Internet training	0.363
Previous courses completed online	0.333
Operating systems and file management training	0.329
Internet applications training	0.309
Years of computer experience	0.124

Table 3. Discriminant Function Summary

Eigenvalue	Canonical Correlation Coefficient <i>R</i>	Coefficient of Determination <i>R</i> ²	Wilks' Lambda	χ^2	<i>d.f.</i>	<i>p</i>
0.099	0.301	0.091	.910	43.466	7	.000*

% of cases correctly classified 79.5.

**p* < .0001.

Table 4. Discriminant Function Summary for Indicator Variables

Indicator of Completion	Standardized Canonical Coefficient	Wilks' Lambda	<i>F</i>	<i>d.f.1</i>	<i>d.f.2</i>	<i>p</i>
Cumulative grade point average	0.592	.953	22.97	1	462	.000**
Class rank	0.504	.960	19.00	1	462	.000**
Searching the Internet training	0.204	.987	6.06	1	462	.014*
Previous courses completed online	0.201	.989	5.10	1	462	.024*
Operating systems/file management training	0.216	.989	4.97	1	462	.026*
Internet applications training	0.176	.991	4.38	1	462	.037*
Years of computer experience	-0.071	.998	0.71	1	462	.401

p* < .05. *p* < .0001.

the discriminant function summary for each indicator variable. The results suggest six pre-entry variables were responsible for discriminating between completing and noncompleting students, including cumulative grade point average ($p = .000$), class rank ($p = .000$), searching the Internet training ($p = .014$), number of previous courses completed online ($p = .024$), operating systems and file management training ($p = .026$), and Internet applications training ($p = .037$).

Conclusions

This study identified pre-entry variables that distinguish individuals who complete university online distance education courses from those who do not. These indicators of completion or noncompletion may help delineate prospective at-risk students. In this study, noncompleting students tended to be lower-division students whose cumulative grade point averages were lower than completing students. Only a few had completed online distance education courses prior to participation in the study. In addition, noncompleting students had taken fewer computer training courses than their counterparts.

Finding prior educational experience, including cumulative grade point average, class rank, and number of previous courses completed online related to retention was anticipated in light of previous research. These findings support the belief that previous involvement in academic programs leads to an evolving student perception that shapes persistence (Włodkowski, Mauldin, and Gahn 2001). Prior educational experience may help students increase their confidence through an awareness of university expectations and a familiarity with the online distance learning milieu.

Of all the pre-entry variables proposed in this study, only one—years of computer experience—did not make an important contribution to the discriminant function. This result is interesting when considering the literature and conventional wisdom suggesting computer experience is related to retention in online courses. However, this study identified a number of prior computer training courses, including (1) searching for information on the Web, (2) operating systems and file management, and (3) Internet applications, as important indicators of completion in online courses. Findings suggest the variable years of computer experience is not as crucial to retention as the type of computer experience. Rather, this study supports the idea that students who have adequate computer training in relevant technologies are more likely to complete online courses since the computer technologies are less likely to impede the learning process.

Implicit in the study is the idea that the results should not be used to exclude or discourage potential students from taking online distance education courses. Rather, the results should help instructors and administrators identify at-risk students and provide them with appropriate training opportunities and guidance. The results of this study provide criteria on which computer training and orientation programs may be developed. Student orientation programs that include training in the use and application of Internet technologies may help students gain experience needed to succeed in online courses.

Recommendations for Future Research

The findings in this study are important but far from conclusive. Findings suggest that prior educational experience and prior computer training are beneficial to students who register in online courses. Additional studies should be conducted using a qualitative methodology to interview students who dropped out of online courses to provide a deeper understanding of these pre-entry variables as well as other variables related to retention.

This study was able to account for 9% of the total variance in explaining or predicting pre-entry variables related to online course completion for the sample of students. Additional quantitative studies should also be conducted to try to explain more of the variance. These studies should include a wider sample of universities and should look at different variables believed to be related to course completion, including instructional and institutional factors.

As online distance education becomes prevalent in higher education institutions, identifying variables that help to distinguish between individuals who complete online courses from those who do not will help instructors and administrators develop and refine systems that serve at-risk students. In the future, the knowledge base that will be called on to help retain students and foster success in online courses will come from continued research that seeks to identify variables that may facilitate or impede persistence in distance education environments.

References

- Belanger, F., and D. H. Jordan. 2000. *Evaluation and implementation of distance learning: Technologies, tools, and techniques*. Hershey, PA: Idea Group.
- Billings, D. M. 1988. A conceptual model of correspondence course completion. *The American Journal of Distance Education* 2 (2): 23–35.

- Carr, S. 2000. As distance education comes of age, the challenge is keeping the students. *The Chronicle of Higher Education* (February): A39.
- Cookson, P. 1990. Persistence in distance education. In *Contemporary issues in American distance education*, ed. M. G. Moore, 192–204. New York: Pergamon.
- Gibson, C. C. 1996. Toward an understanding of academic self-concept in distance education. *The American Journal of Distance Education* 10 (1): 23–36.
- Hansen, B. A. 2000. Increasing person-environment fit as a function to increase adult learner success rates in distance education. Ph.D. diss., University of Wyoming, Laramie.
- Kearsley, G. 2000. *Online education: Learning and teaching in cyberspace*. Belmont, CA: Wadsworth.
- Kember, D. 1989. A longitudinal process model of drop-out from distance education. *Journal of Higher Education* 60 (3): 278–301.
- Lim, C. K. 2001. Computer self-efficacy, academic self-concept, and other predictors of satisfaction and future participation of adult distance learners. *The American Journal of Distance Education* 15 (2): 41–51.
- Osborn, V. 2001. Identifying at-risk students in videoconferencing and Web-based distance education. *The American Journal of Distance Education* 15 (1): 41–54.
- Phipps, R., and J. Merisotis. 1999. *What's the difference? A review of contemporary research on the effectiveness of distance learning in higher education*. Washington, DC: The Institute of Higher Education Policy.
- Tinto, V. 1975. Dropout from higher education: A theoretical synthesis of recent research. *Review of Education Research* 45 (1): 89–125.
- Wlodkowski, R., J. E. Mauldin, and S. W. Gahn. 2001. Learning in the fast lane: Adult learners' persistence and success in accelerated college program. *New Agenda Series* 4 (1): 4–21. Indianapolis, IN: Lumina Foundation for Education.